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# An overview of reliability models and methods for distribution systems with renewable energy distributed generation

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ABSTRACT

This paper presents a review of reliability models and methods for estimating renewable energy resources influence on electrical generation availability. These models and methods may be used to evaluate the impacts on the distribution systems reliability of distributed generation integration, especially when they are based on renewable energy sources. For such, the paper presents the main characteristics of renewable resources models that have been developed for wind, small hydro, solar and biomass, and presents the main methods for reliability evaluation of distribution systems with such resources integrated. These evaluation methods may be based on analytical techniques, Monte Carlo simulation or hybrid approaches. The impact of distributed generation on the reliability of electric distribution systems depends mainly on the operational mode and the energy source in which it is based. The most uncertain case is related to generation based on renewable energy of intermittent nature where the generation availability depends on the availability of the energy source and the availability of the generating unit.



**Contents**



## 1. Introduction

Distributed generation (DG) is concerned with small generating units installed in strategic points of the distribution or sub-transmission systems and close to load centers. DG can be used in an isolated way, supplying the consumer's local demand, or in an integrated way, supplying energy to the remaining of the electric system. In distribution systems, DG can provide benefits for the consumers as well as for the utilities, especially in sites where the central generation is impracticable or where there are deficiencies in the transmission system. DG may also be named as Embedded Generation or Distributed Energy Resources (DER). The main advantages expected from the connection of DG to the electric system are:

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- Transmission costs reduction by allocation of generation closer to the load.
- Reduced construction time and investment cost of smaller plants.
- Adequacy to the sector deregulation and competition policy.

However, the utilities obligation of providing access to the distribution network to the Independent Producers that want to install DG units confronts with the need of controlling the network and guaranteeing appropriate security and reliability levels. The uncertainties involved in system planning and operation become larger than in the past, especially when renewable energy sources are used.

A significant increase in the use of renewable energy sources for power system generation is being observed all over the world. A number of strategic and commercial issues combined are responsible for this interest, mainly [1]:

- Reduction of greenhouse gas emission.
- Diversification of the energy sources matrix.
- Need for expansion of the generation offer to attend the forecasted growing demand.

Usually, government programs stimulate the investment in generation plants based on renewable energy, such as, wind, small hydro, solar, and biomass. Renewable sources, however, tend to have smaller energy density when compared to fossil fuels and, for that reason, the plants are smaller and geographically more distributed. When based on intermittent energy sources, they cannot be pre-dispatched by the utility but only according to the availability of the primary energy source. The large uncertainty present in this kind of generation influences strongly on the system reliability.

For that reason, intermittent energy has disadvantages as a regular energy source and is considered less reliable than conventional sources. The amount of energy daily available can vary a lot from a season to another at the same site and its use is limited only to adequate sites.

The integration of DG base on renewable energy of intermittent nature can cause positive and negative impacts to the utility distribution network. Uncertainties related to DG are due to two main aspects: the intermittent nature of the primary energy source and the possible unavailability of the unit when it is required to generate. The combination of these aspects may lead to generation deficit, which can heavily compromise the security, reliability and quality of power supply. The increase in the size and complexity of distribution systems, together with the necessity of attending the demand in an economic and reliable way, requires the assessment of the random nature of network failures and generation outages, given that such events can lead to interruptions in electricity supply. However, nowadays it is undoubted that DG is an important alternative for generation expansion planning [2].

This paper intends to address the impacts on the distribution systems reliability of distributed generation integration, especially when they are based on renewable energy sources. For such, the paper reports the evolution of some renewable resources models that have been developed (for wind, small hydro, solar and biomass) and details the general models for reliability evaluation of distribution systems with such resources integrated, based on analytical method, Monte Carlo simulation or hybrid models. In summary, it can be said that the impact of distributed generation on the reliability of electric distribution systems depends mainly on two aspects:

- The operational mode and purpose of its connection to the system.
- The energy source in which it is based, especially if renewable and intermittent.

## 2. Operational mode of DG and its impact on reliability

There are mainly three modes of DG connection to the network, each one with a different purpose and impact on system reliability:

1. A simple example of DG use is as generation backup, in which the unit is operated in the case of local utility supply interruptions. In a system that includes DG, load transfer to other feeders via switches operation can be performed in interruption situation in order to keep customers supply. If the DG units are correctly coordinated, they can have a positive impact on distribution system reliability [3].
2. Another DG application is the injection of the excess power of the unit generation in the distribution network that may occur when the DG capacity is higher than the necessary to attend the local loads. The energy that is injected in the network is measured and the consumer has to pay only for the difference between the energy consumed from the distribution utility and the amount injected in the network. In this case, there is no benefit for the system reliability.
3. The third mode is when the DG is operating in parallel with the main system. In this case, new considerations must be introduced for reliability modeling. The simplest alternative is to model DG as a negative power injection, independent of the system voltage at the terminal bus. To model DG units as negative loads can have a positive impact in reliability since it will represent a reduction on the load demand. However, better models need to be used in order to represent the DG, especially when they are based on intermittent renewable energy, to evaluate the influence of such units on the system reliability. That is what the next section will deal with.

## 3. Renewable resources modeling

The renewable energy in which the DG is based has fundamental influence on reliability. Units based on non-intermittent and storable energy sources, such as biomass, can be more easily represented, since energy can be considered available in reliability studies. The only issue usually considered for unavailability of generation is the failure of the generating unit. This kind of DG tends to be more reliable.

On the other hand, the units based on intermittent and not storable energy sources, such as wind, small hydro and solar, require a more complex model in reliability studies, where the energy availability also needs to be represented. The unavailability of generation of this kind of DG can be caused by unavailability of energy, failure of the generating unit or insufficient level of available energy. The availability model of energy normally requires an analysis of time series of measurements on the energy input (wind speed, solar radiation, etc.). Therefore, the generation availability must be modeled by the combination of the availability model of energy and the availability model of generating unit.

### 3.1. Wind generation

Wind energy can be considered as the renewable energy source with the most successful exploration in the world. However, wind generation has disadvantages as a regular source of energy in terms of reliability. The daily amount of energy available can vary widely and its use is limited to places of high and relatively constant winds. The connection of a growing number of wind farms to the electrical systems implies in the need to study their effects. The operating

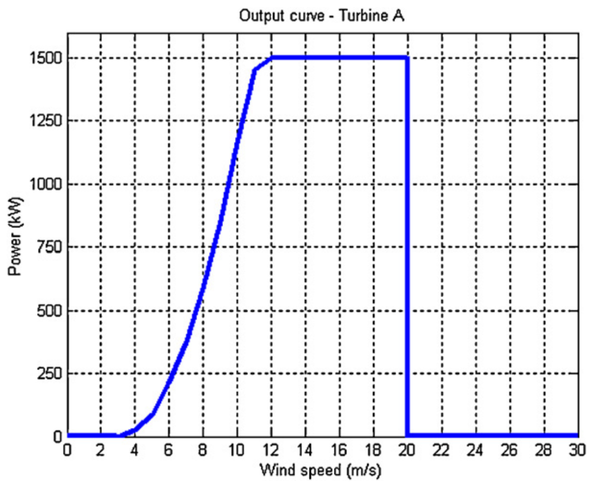


**Fig. 1.** Power curve of an wind turbine.

characteristics of the wind farm, heavily dependent on the local regime of wind, imply that the conventional power plant stochastic model is inappropriate to be applied to it.

In [4] a reliability model that considers all factors that influence the generation of a wind farm was developed, modeling the stochastic behavior of wind velocity, the operating behavior of turbines and the characteristic of power generated by wind turbines.

The power extracted by the wind turbine from an air flow of density $\rho$, moving at speed $v$, perpendicular to a traverse section of a cylinder of area $A$, can be expressed as (1):

$$P = \frac{1}{2} C_p \rho A v^3 \tag{1}$$

where $C_p$ is the power coefficient of the turbine. As the generation is proportional to the cube of the speed of the wind, the variations of power generation can be very high.

In order to allow some control of the generation, the stall and pitch controls are introduced. Since very high speeds can provoke damages to the turbine, the control device limits the operation of the turbine to a cut out speed. This speed is around 20–25 m/s. On the other hand, low speeds produce very low power that may be insufficient for the generator start up. The cut in speed for the initial operation of the turbine is around 3–5 m/s. For values out of the interval between cut in and cut out speeds, the generated power is null. The curve of power generated by a wind turbine represents its operation characteristic $P(v)$, as shown in Fig. 1.

The wind turbine is modeled as a two states Markov process. When it is in the operative state, the value of power generation is determined by the wind speed and by its $P(v)$ characteristic. The transitions between the operative and failed states are characterized by the failure ($\lambda$) and repair ($\mu$) rates. The mean time to repair ($r = 1/\mu$) of the turbine is a function of the climatic conditions, of the affected part of the turbine, of the operation logistics and plant maintenance program and of the speed of the wind in the instant of the failure.

For a plant with $N$ wind turbines, the number of possible states raises to $2^N$. Fig. 2 shows the state space diagrams for one and two different turbines, with failure rates $\lambda_1$ and $\lambda_2$ and repair rates $\mu_1$ and $\mu_2$.

The behavior of the wind is modeled as a stochastic process, where the random variable is the speed of the wind. The schematic diagram of the behavior of the wind is represented by a Markov chain, is shown in Fig. 3. The wind states are represented in a growing speed order and the transition from state $j-1$ to state $j$ is quantified by the transition rate $\lambda_{j-1 \cdot j}$.

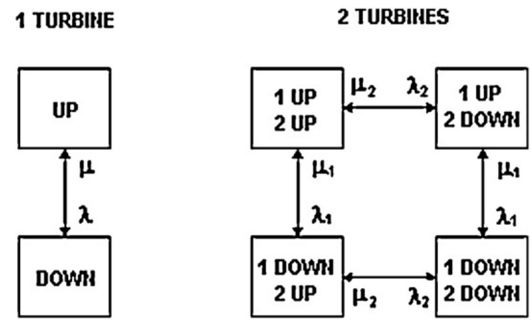


**Fig. 2.** State space diagrams for one and two wind turbines.

For a process to be adequately represented by a Markov chain, it is necessary that the occurrence of the next state only depends on the actual state. Besides, the process needs to be stationary, with constant behavior during the whole period, independently of the chosen starting point. This implies in considering constant transition rates between states during the whole process [5]. Due to the seasonal variations of the wind, the mean speed and standard deviation are not constant along a period, such as a day, a month or even a season. Therefore, in fact, the wind is not a stationary process. However, this effect can be disregarded if the wind data used in the study do not follow a specific trend of any particular season and if the amount of data is sufficiently large, representing a large period of time, such as years [6]. Besides, those effects are less important when evaluating the long term expected values which are calculated in reliability studies. In that sense, it is possible to accurately represent the wind speed by a stationary Markov process, with constant transition rates, if only the limiting state values are of interest.

Due to the large number of wind speed states present in long time series, the representation of all of them in a model can become unfeasible. For that reason, the statistical clustering technique $K$-means [7] was adopted for clustering them in a smaller number of states. Fig. 4 shows a piece of an actual wind speed time series with 40 measurements and the series obtained after the clustering in 4 states.

The wind farm model is obtained by the combination of the turbine and the wind models and is represented by the state space diagram shown in Fig. 5. The transitions between the operative and failed states of the group of turbines are represented by the failure and repair rates, $\lambda_1$, $\lambda_2$, $\mu_1$ and $\mu_2$. The speed of the wind are represented in states I and II and the transitions between them are represented by the rates $\lambda_{ij}$, where $i$ represents the initial and $j$ the final wind states. This way, eight different states are present for

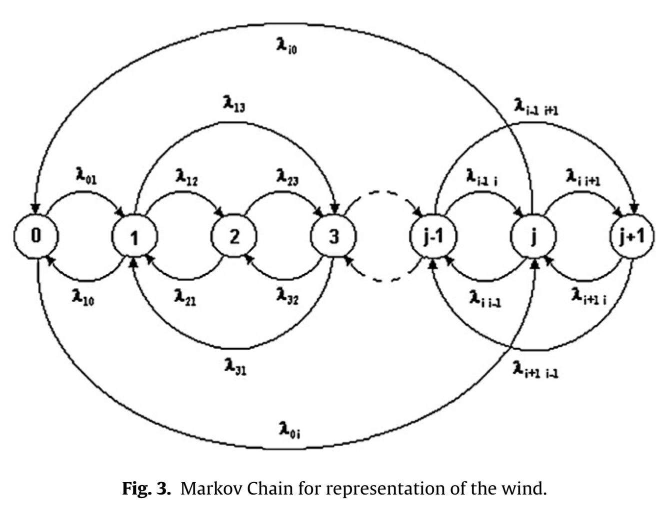

**Fig. 3.** Markov Chain for representation of the wind.

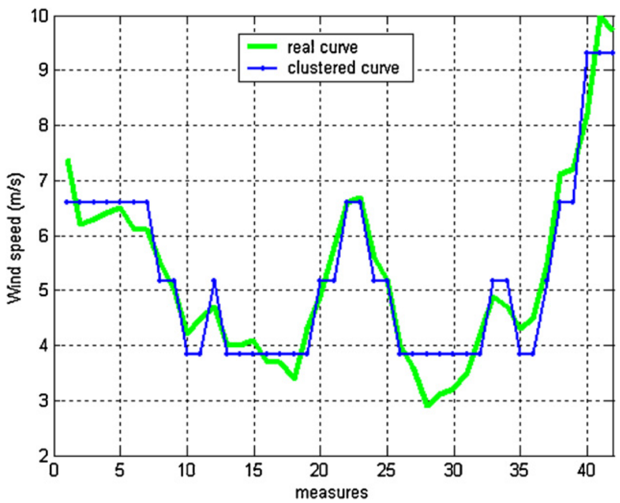


**Fig. 4.** Piece of a time series of wind speed clustered in 4 states.

the example of two turbines with two wind states. For $N$ turbines and $n$ wind speed states, the resulting number of states for the wind farm is $2^N n$.

### 3.2. Small hydro generation

In large hydroelectric generation reliability studies, where the reservoir is large enough to guarantee the availability of energy, through a constant regime of inflows, it is usual to consider the energy source for generation as always available. This implies that the only cause of generation unavailability is the failure of a generation unit. However, in most of the small hydro power plants (SHPP), where a reservoir does not exist or is very small to guarantee a full regularization, the energy availability cannot be considered 100% reliable.

In [8], a model for evaluating SHPP energy availability was developed to be used for reliability studies. The model considers the uncertainties of rivers inflows, the hydraulic turbine characteristic and the generating units operation.

The historical data of hydro operation contains a long time series with the values of inflows corresponding to the monthly mean values registered in the past. Fig. 6 shows the inflow values in the

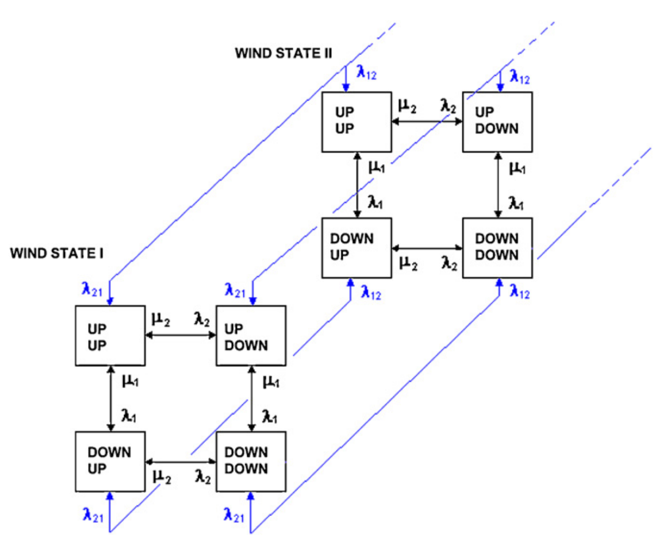


**Fig. 5.** State space diagram of a wind farm.

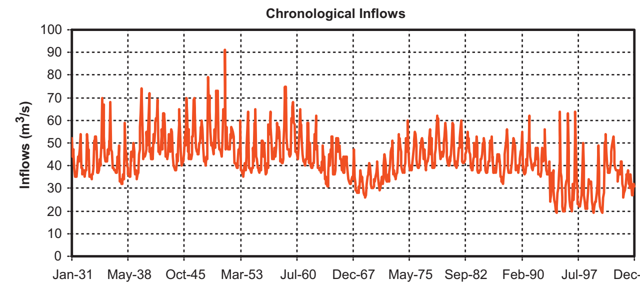


**Fig. 6.** River chronological inflows.

chronological order from January 1931 until December 2004 in $m^3/s$ for a river in Brazil.

The river inflow is modeled as a stochastic process, where the random variable is the inflow value. The Markov chain model is adopted, were each state represents a different inflow value, and the transition rates between different states are calculated. The river inflow model is shown in Fig. 7, where the transition from state $i$ to state $j$ is quantified by the transition rate $\lambda_{ij}$. For the same reason explained for the wind time series, it is possible to accurately represent the inflow by a stationary Markov process, with constant transition rates. An inflow time series usually contains many different inflow values and the statistical clustering techniques $K$-means was also adopted to reduce the number of inflow states to be represented in the model.

The efficiency of a hydraulic turbine is a function of many variables, such as nominal power of the turbine, type of the turbine, and percentage of turbinated fluid. There are 3 main types of turbine: Francis, Kaplan and Pelton. Fig. 8 shows the efficiency curve of a Francis turbine, as an example.

The generated power of a hydraulic generation unit can be calculated by (2):

$$P = \gamma \cdot Q \cdot H \cdot \eta_T \cdot \eta_G \qquad (2)$$

where $P$ is the power (W); $\gamma$ is the specific weight of the water (9810 N/m$^3$); $Q$ is the inflow (m$^3$/s); $H$ is the water fall height (m); $\eta_T$ is the efficiency of the turbine (%); $\eta_G$ is the efficiency of the generator (%).

The electric generators used in SHPP are synchronous machines that produce electric power in alternating current. The electric generator is modeled by a two states Markov model, as shown in Fig. 2.

The SHPP generation availability model combines the river inflow model, the turbine efficiency curve and the generator model and is represented by a multiple states diagram, as shown in Fig. 9. The transition processes of the two stochastic models are considered as independent events, meaning that variations of the river inflow are not influenced by the generator failure and vice versa. The inflow clustered states are represented in states 1 to $N$ and the transitions between them are represented by the rates $\lambda_{ij}$, while the transitions between the generator up and down states are represented by $\lambda$ and $\mu$. The down states can be aggregated into just one, producing a SHPP model with $N+1$ different states: $N$ up and one down.

### 3.3. Solar generation

Solar energy is also presenting a quick growth and success usage around the world, mostly due to the combination of being a clean renewable source with the reduction of the solar cells cost. However, like the wind, its availability may be low due to the intermittency inherent to sunlight. For example, in many regions, half the day there is little or even no generation due to variation of

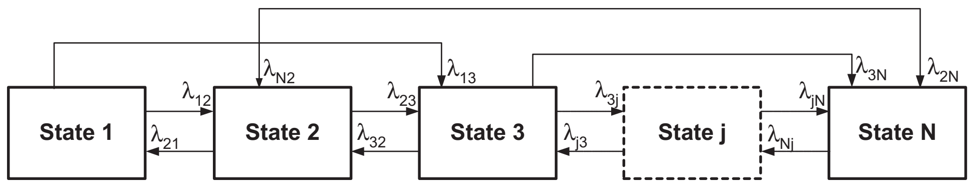


**Fig. 7.** Markov model of river inflow.

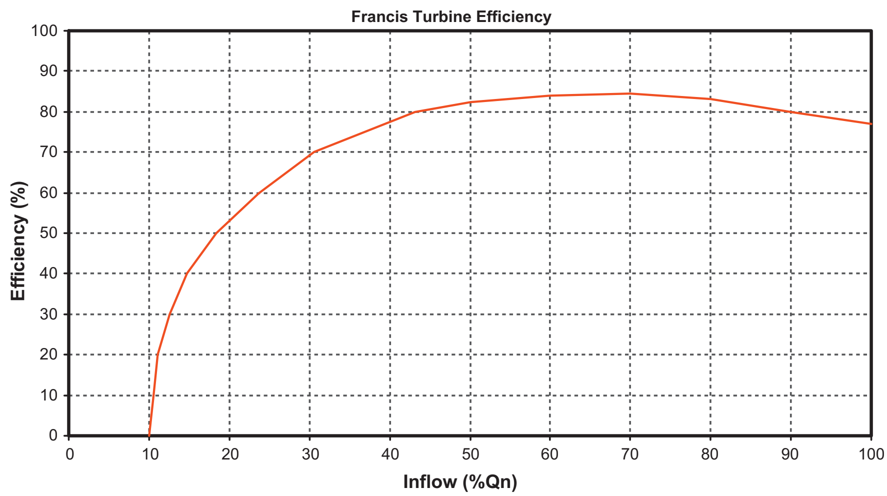


**Fig. 8.** Francis turbine efficiency curve.

solar radiation. The solar radiation varies randomly depending on various aspects, like the weather being cloudy or not, the environmental conditions of the region, etc. In order to reduce this randomness, storage systems must be used to provide power at night, for example.

In [9] a method for evaluating the reliability of a power system with solar generators is presented. The solar generation is modeled by a multistate model based on data obtained in Korea. The conventional power plants model with two operating states (success or failure) is not suitable for photovoltaic plants. In the probability distribution of solar radiation at any site, there is a clear state of failure, when the radiation is zero, and multiple values of radiation that generate different amounts of power. Therefore, to group them into a single success state would be an error, because the power supply varies greatly according to the time of the day and the seasons. The most appropriate model is then a multiple states model as shown in Fig. 10.

The power generation associated with each state is calculated based on (3), which is applied to the data of solar radiation at the plant site, as shown in Fig. 11.

$$
\begin{array}{lll}
P_i(G_{bi}) & = P_{sn}(G_{bi}^2/(G_{std}R_c)), & 0 < G_{bi} < R_c \\
 & = P_{sn}(G_{bi}/G_{std}), & R_c < G_{bi} < G_{std} \\
 & = P_{sn}, & G_{bi} > G_{std}
\end{array}
\qquad (3)
$$

where $P_i$ is the power generation (MW); $G_{bi}$ is the estimated solar radiation value $i$ (W/m$^2$); $G_{std}$ is the solar radiation valor at stardard environment (usually 1000) (W/m$^2$); $R_c$ is the solar radiation conventional valor (usually 150) (W/m$^2$); $P_{sn}$ is the generation capacity of solar plant (MW).

### *3.4. Biomass generation*

From the viewpoint of energy generation, biomass is any organic material that can be converted into mechanical, thermal or

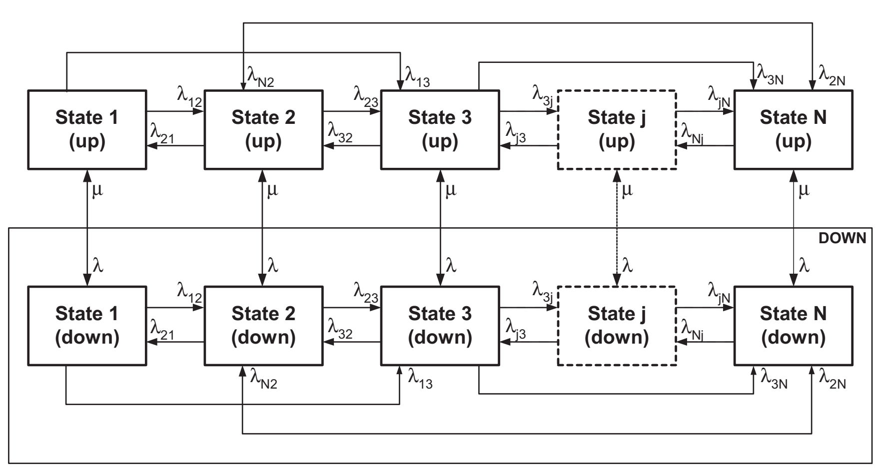


**Fig. 9.** SHPP generation model.

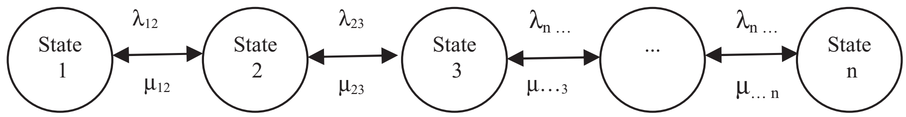


**Fig. 10.** Solar plant model.

electrical energy. According to their origin, it can be: forest (wood, mainly), agriculture (soybeans, rice and sugar cane, among others) and municipal and industrial wastes (solid or liquid, such as garbage). The products obtained depend on both the raw material used (the potential energy varies from type to type) and process technology to obtain energy.

There are two ways of generating energy from biomass: direct combustion and gasification technologies, which produce, respectively, steam and gas as fuel. The generation of electricity through direct combustion of biomass occurs in conventional power plants using steam turbines. The generation is based on the Rankine Cycle. The gasification technology is the conversion of any liquid or solid fuel such as biomass into an energy gas by partial oxidation at high temperature. This conversion, performed in gasifiers, produces a fuel gas that can be used either in gas turbines or in burners and boilers for steam generation. These technologies have significant differences in terms of electricity generation, investment costs, operational sophistication, technological expertise and commercial availability. Both types of technology are also applied in cogeneration processes, traditionally used by industries.

The procedures for obtaining energy from biomass are characterized by low efficiency and the need for large volumes of raw material. The large-scale production of electrical energy is related to the periods of agricultural crops, since it uses the agro waste (corn cobs and straw, sugarcane bagasse, soybean and rice hulls, etc.). Thus, the time series of energy extracted from biomass has a periodicity that can vary from months to seasons, and even in the months between harvests, there is still stored raw material. Thus, the intermittency of energy related to biomass generation can be considered very low or in some cases, negligible.

Therefore, biomass generation can be considered as one type of thermal generation with very low intermittency. The biomass based thermal generation may be represented by a three states model (operation, repair and derated states), as shown in Fig. 12. In this model, the derated state may represent the failure of some components that does not take the unit from operation but instead reduces power generation or it may represent the power availability for periods between harvests, when the biomass stock may be smaller and, consequently, the capacity is reduced.

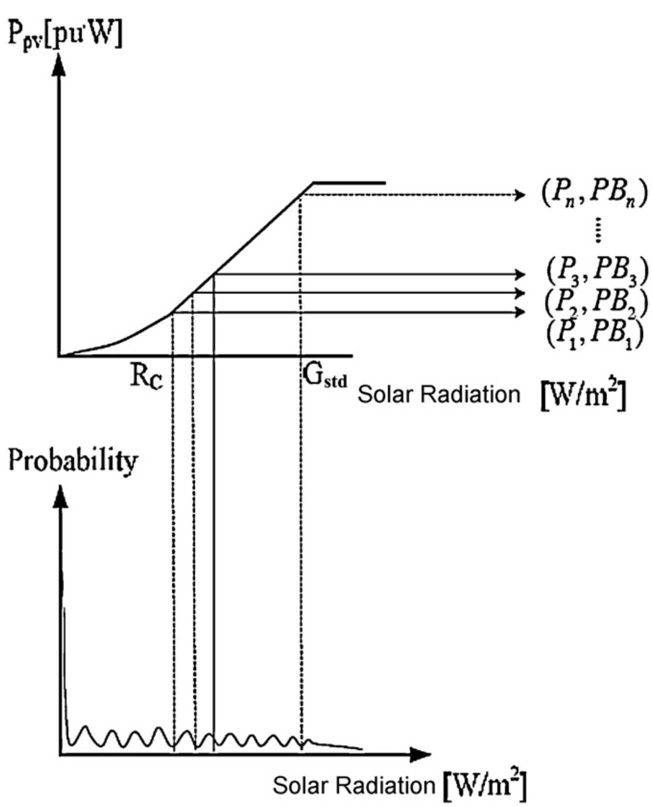


**Fig. 11.** Relation between solar radiation and power generation.

## 4. Distribution system reliability evaluation with renewable generation

In general, there are two different classes of methods for distribution system reliability evaluation with embedded renewable generation. The first class is based on the analytical method and is applicable to generation units of non-intermittent energy sources. The second class is based on Monte Carlo simulation and is adequate to represent generation units of intermittent energy sources and also to aggregate the load variation curve. Hybrid methods that combine the advantages of each of the previous one may also be used. Details of these methods for evaluation of distribution systems with such resources are presented next.

### 4.1. Analytical methods

Analytical methods for reliability indices calculation in radial networks [10] may be adapted to be used for distribution system reliability evaluation in the presence of DG. However, the protection system selectivity needs to be guaranteed when multiple generation sources are distributed along the network, in order not to harm the reliability of the system.

Most of the methodologies based on the analytical method consider that the DG can supply all or part of the load in the case of main source unavailability [11]. It is also considered that the occurrence of a failure causes the disconnection of both the main supply and the DG from the system, as it is common practice for some current distribution utilities. After the isolation of the fault via proper switches operation, the DG is re-connected to the system. In this way, the frequency related indices are not modified by the presence of DG. On the other hand, there is a reduction on duration related indices since part of the load can be attended by DG while the main supply interruption cause is being repaired. This benefit is greater if the DG energy source is based on non-intermittent energy sources (e.g. gas, diesel, biomass). For variable energy sources (e.g. wind,

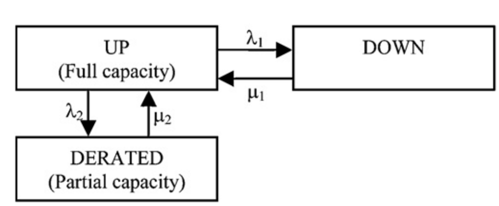


**Fig. 12.** Biomass generation model.

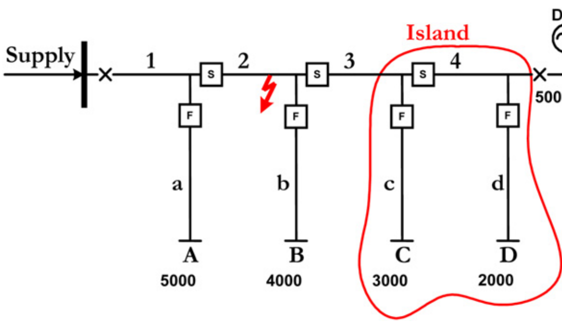


**Fig. 13.** Reliability benefit due to DG in islanded operation.

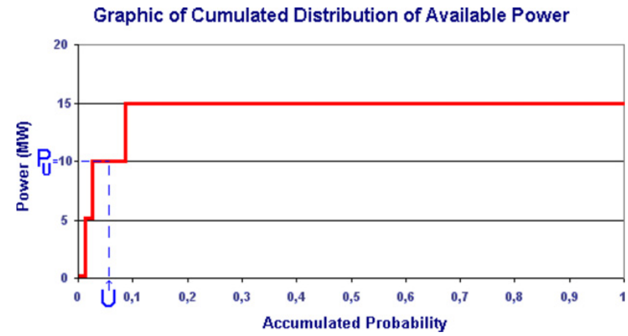


**Fig. 14.** Cumulated distribution function of available power.

SHPP, solar) a more complex evaluation method is recommended, as will be described in the next section.

In this approach, the DG is modeled similarly as a back feed with transfer restriction equal to the DG unit capacity. The islanded operation mode is considered as a means to make the most of distributed generation. The load block reliability indices are calculated comparing the block installed load with the total capacity of DG directly connected to the block (or island). If the DG capacity is higher than the load, the load block unavailability duration is only the time for isolating the fault and connecting the DG. Otherwise, the block unavailability duration will be the repair time of the failed component. Fig. 13 shows an example where loads C and D may be supplied by the DG unit, operating in islanded mode, in the case of a failure in Section 2 isolated by the opening the isolator on Section 3.

### 4.2. Monte Carlo simulation

Probabilistic reliability evaluation of distribution system can be performed using two different representations of the system: states space and chronological representation [12]. In the states space representation, the states of the system are randomly sampled by Non-Sequential Monte Carlo Simulation (MCS). In the chronological representation, the states of the components are sequentially sampled simulating the chronology of the stochastic process of system operation, by Sequential MCS.

#### 4.2.1. Non-Sequential Monte Carlo Simulation

In Non-Sequential MCS, the states of the system are obtained by sampling the components states space and it is not concerned with the chronology of the events. The states of the system depend on the combination of the states of all components, which are obtained by sampling the probability distribution of each component states.

For the DG units, the power generation value may be determined by sampling the Cumulated Distribution Function (CDF) of available power [13], which is obtained from the renewable resources models described in the previous section. Fig. 14 shows an example of a CDF of available power of a multiple states model generation. The sampling procedure consists of generating a random variable $U$, uniformly distributed in the interval [0,1], and then obtaining the DG power output ($P_U$) by the Inverse Transformation Method.

#### 4.2.2. Sequential Monte Carlo Simulation

In Sequential MCS, the sampled states preserve the chronological characteristics of the system operation. For such, annual synthetic series are generated by the combination of the system components states transition processes and the chronological variation of the time varying elements, such as the load and intermittent generation. Theoretically, Sequential MCS is the technique that produces the most correct results in reliability evaluation and therefore is commonly adopted as reference for validation of other techniques.

The states of the distribution network are sequentially sampled in order to create a synthetic series of operation/failure states, based on the probability distribution of the states duration. For any component modeled in two states, such as distribution transformers and feeders, the synthetic series of operation and failure states have a characteristic similar to Fig. 15.

For the DG units based on intermittent energy sources, the representation is straightforward in sequential MCS, by merely considering the time series of the primary energy. At each simulation time step, the energy source value is applied to the power generation characteristic of the energy conversion device (wind or hydro turbine, solar cell, etc.) and then combined with the generator unit stochastic model, in order to obtain the final generated power value.

The favorable factor of using Non-Sequential MCS instead of the sequential one is the much smaller computational effort demanded, while the main limitation is the fact of losing the chronological aspects of the simulation, which may be important in studies involving renewable generation.

### 4.3. Hybrid methods

Some methods combine the simplicity of the analytical method with the capacity of stochastic phenomena representation of Monte Carlo simulation. In [14] the reliability evaluation is performed using a hybrid method that combines an analytical method to evaluate the network with random sampling techniques to represent the intermittent generation. This allows considering the impact of intermittent energy sources in the system reliability indices. Since the basis in this proposal is the analytical method, the simulation is performed as follows:

1. Sample the generation availability based on the CDF of each energy source (wind, SHPP, solar, etc.).
2. With the generation sampled values, calculate the network reliability indices using the analytical method.
3. This process is repeated until the coefficient of variation ($\alpha$) is less than 5% for all indices or the maximum number of iterations is reached.

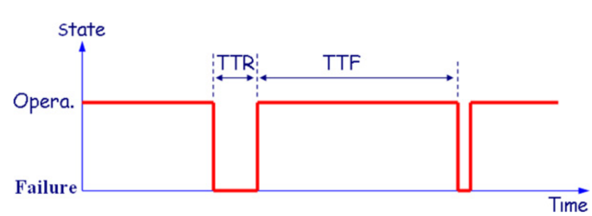


**Fig. 15.** Synthetic series of operation of two states components.

4. At the end, the average values are calculated for each reliability index.

At any iteration, all generation values are sampled. With these values, failure rates and unavailability are calculated for each load point. When all points have been calculated, the reliability indices are calculated for the system at that iteration. It is verified if the coefficient of variation is less than a specified value for all indices and, if so, the results are the values obtained for each index. If not, the generations are sampled again and the process is repeated.

### 4.4. General considerations

For distribution system reliability evaluation, some considerations are assumed regarding the network operation, which are: the distribution substation and transmission system are considered 100% reliable and the failure of operation of the protection equipments is usually disregarded. For inclusion of DG units in the reliability evaluation methods, the representation of the following aspects must be considered:

- Uncertainty of renewable energy sources availability.
- Chronological variation of the load.
- Protection and reconfiguration devices in the network.
- Possibility of islanded mode operation.
- Load shedding and load transfer prioritization polices.

The adequacy of the distribution system in terms of voltage and transfer capacity is evaluated by the solution of a power flow problem. The reliability indexes calculated are the load point average failure rate ($\lambda_L$) and the annual outage time ($U_L$) and the system indices SAIFI, SAIDI, EENS and ECOST [10].

The main corrective measures that may be considered in order to eliminate voltage and capacity violation and enhance reliability are:

(a) *Switching*: opening of protection and switching devices in order to isolate the failed blocks.
(b) *Load transfer between feeders*: after isolating the failed blocks, part of the load may be transferred to other feeder by closing normally open switch.
(c) *Islanded operation by DG*: after isolating the failed blocks, an island may be fed by DG if the total load is smaller than the DG capacity.
(d) *Load shedding priority*: The load shedding policy considers higher priority value for more important loads (hospital, etc.). If the island load is higher than the DG capacity, part of the load is shed according to the priority policy.

## 5. Conclusion

The results obtained with the combination of the reliability models of renewable generation with the different evaluation methods are published on the cited papers and allows the conclusion that DG enhances the reliability of distribution systems, especially if islanded operation is considered. However, when the generation is based on intermittent energy sources, the benefit is reduced and can even be negligible if not properly planned. The importance of having a good representation of the power supplied by units whose primary sources are of intermittent nature is clear on those results. The representation of these sources by multiple states models that take into consideration the energy time series allows a simple and close to reality reliability evaluation.

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